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Abstract

A&E overcrowding is an important problem since many are not seen in a sufficiently quick time. There is evidence that the situation can be improved without adding additional resources by diverting would-be A&E patients to alternative centres of urgent care, for example, Minor Injury Units (MIUs). The aim of this paper is to investigate how access to information on waiting times may influence decision making. We collect laboratory data where subjects are offered a choice between receiving treatment at A&E and MIU. The subjects face a random delay at the A&E but a known wait at the MIU. We manipulate the information that the subjects receive from the probabilities (risk) of the different waiting times at the A&E from known probabilities to merely a vague indication of the waiting time (ambiguity). We find that subjects demonstrate a strong preference for the A&E. Subjects display risk neutrality for the A&E waiting time but are ambiguity averse when waiting times are relatively short and ambiguity-seeking when waiting times are relatively long. This indicates that perhaps partial revelation of waiting times may be optimal. Our research will inform stakeholder decision-making at the operational level (such as individual UK National Health Service (NHS) Trusts) about strategy regarding the release of timing information.

Keywords: Health decisions, waiting times, ambiguity aversion.

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1 Introduction

A&E wait times have increased substantially over recent years. In the UK, it is expected that 95% of patients should be assessed, treated, then either admitted, transferred or discharged within four hours of arriving. This is commonly referred to as the four-hour standard. The National Health Service (NHS) has not met this standard in emergency departments nationally since 2013/14, and the standard has been missed every month since July 2015 (King's Fund, 2020). The four-hour standard also applies to healthcare facilities which treat non-life-threatening conditions like sprain and fractures, cuts and other minor injuries. These facilities are known as Minor Injury Units (MIUs). Although the context presented here is the UK, A&E overcrowding affects many countries (Di Somma et al., 2017). It is an important problem from the perspective of individual patients since they are not seen in a sufficiently quick time. It is also a significant problem for A&E departments as resources that are primarily meant for patients with life-threatening conditions, e.g., loss of consciousness and chest pain, are being used for treating patients who could have been seen at a MIU. There is evidence that the situation can be improved without adding additional resources by diverting would-be A&E patients to alternative centres of care, for example, MIUs.

The aim of this paper is to investigate if access to information on A&E/MIU waiting times influence decision making. The real-world implication of the work is that it seeks to empower patients requiring urgent (but not emergency) care by releasing wait time, with the overall objective of enabling a shift of demand from A&E to MIUs. Although release of wait time data is not new, to the best of our knowledge there is no existing study that has experimentally measured the indifference point between the A&E and the MUI waiting times. (The indifference point is the point at which patients of switching from an A&E to an MIU for longer waiting times at the A&E.) In the context of our work, the indifference point assumes further importance as this would allow the controlled release of information (e.g., whether to provide precise wait time or be vague - subsequently defined as the granularity of data), with the overarching objective to nudge non-urgent patients to choose MIUs over A&Es.

This paper builds on existing work of using an app to nudge patients towards MIUs by ordering the listing of A&Es and MIUs based on combined wait time and travel time. The existing implementation of this work is through a cloud-based platform called NHSquicker (https://nhsquicker.co.uk/; Health Care IMPACT Network, 2021), which receives real-time information on waiting time from 27 A&E departments and MIUs located in the South West of England. This intervention provides an indirect suggestion for patients to consider services that may be further away, but when both wait time and travel time are taken into account, they may be still seen quicker.

As noted earlier, the crowding in A&E (measured through current wait time) is experienced by most hospital trusts in England. Due to this delay, for most of the day, there is a high likelihood of MIUs being listed first on the NHSquicker App, thus subtly prompting the patient to consider it as an attractive option (the nudge).

As such, this intervention ensures that, for most part of the day, there is an increasingly likelihood of MIUs being listed earlier, thus subtly prompting the patient to consider this option (the nudge). The NHSquicker App (subsequently referred to as 'the App'), which serves as the front-end of this platform, reports A&E and MIU wait time data based on user's current location. The work reported in this paper will complement this existing work by informing the parameters of the aforementioned nudge algorithm, and which will be implemented in a future version of NHSquicker. More specifically, since the time at which the decision maker is indifferent between A&E and MIU, is the point at which the she switches to MIU, the higher the indifference point is (in terms of A&E time) the more likely A&E will be selected. Therefore, by manipulating the information less (more) if we are able to observe higher (lower) indifference points and can deduce that with more information more decision makers will select MIU.

In order to study the effect of information on choice of the patients for either A&E or MIU, we analyse decisions made by subjects in a laboratory experiment. Our experiment replicates the decision faced by patients using the App. The analysis is based on subjects, who represent the App users, choosing between A&E and MIU in three situations: (a) subjects know the waiting time (complete information) at the two places, (b) waiting time for A&E is uncertain but subjects know the probability, while the time at MIU is deterministic and finally, and (c) the A&E waiting time is uncertain but subjects do not know the probability, while again the MIU waiting is deterministic. Hence, the situations vary by the information subjects have regarding the A&E waiting time.

Our study links with the decision-making theory and experiments, which has documented that decision-makers may choose differently in case they are unaware of the probability distribution of the uncertain outcome compared to when they know the probability distribution (see Ellsberg, 1961, for the seminal work in the area). While the former is generally referred to as ambiguity, the latter is referred to as risk. For our analysis of design on information for the A&E and MIU choice, we frame the decision as a choice in complete information, decisions when the choice is ambiguous and decision when the choice is risky. Given the choice, we hypothesise that decision makers will prefer A&E if both A&E and the MIU have the same waiting time, decision makers are risk averse, and decision-makers are ambiguity averse or pessimistic. The analysis was designed to inform us if informing the decision makers about the probability of the possible waiting times (more information) will reduce the choice in favour of the A&E.

Our analysis adds to the evidence collected on decision making under ambiguity. Halevy (2007) and Abdellaoui, Klibanoff and Placido (2015) have shown that there are individuals who behave differently faced with ambiguity and can be have different ambiguity attitudes, can either be ambiguity loving or averse. Interestingly Kocher, Lahno and Trautmann (2018) find that decision makers can be ambiguity averse in the gain domain but neutral or loving in the loss domain. Chen, Katuščák, and Ozdenoren (2007), and Kelsey and La Roux (2017) have shown that ambiguity influences strategic decisions in auctions and weakest link games. More recently Li, Turmunkh and Wakker (2019)) has shown that individuals are less likely to trust if they are ambiguity averse. We look at individual decision-making replicating a practical everyday choice decision makers make.

We collect and study laboratory data where subject are offered a choice between receiving treatment at A&E and MIU for the same ailment. The subjects face a random time to be seen at the A&E but a known time at the MIU. We find that subjects demonstrate a strong preference for the A&E. Subjects display risk neutrality for the A&E waiting time but are ambiguity averse when waiting times are relatively short and ambiguity-seeking when waiting times are relatively long. This indicates that perhaps partial revelation of waiting times may be optimal.

The paper is organised as follows, in the next section we describe the motivation of our experiment stemming from the crowding in A&E in NHS and the App, next we develop the theory and hypotheses. After the hypotheses we describe the design followed by the results and then we conclude.

2 Motivation

The UK National Health Service (NHS) is a publicly-funded healthcare service which is free at the point of delivery. The NHS provides patients with primary care through mainly General

Practitioner-led surgeries (the first point of contact), secondary care (this could be either elective care such as surgeries or urgent and emergency care provided at hospitals and other community-based healthcare centres like the MIUs) and tertiary care (specialised treatment facilities). In 2019/20, the NHS in England had a budget of over £140 billion and there were 217 NHS providers of secondary and tertiary care (https://nhsproviders.org/). Based on the level of secondary care provided, the emergency and urgent care facilities are classified into Type 1, Type 2 and Type 3 centres. Type 1 centres are the traditional A&E departments that are consultant-led, 24-hour facilities; Type 2 are facilities that provide one single treatment, e.g., dentists, and Type 3 are the MIUs. The focus of this paper is on secondary care and, in particular, the Type 1 A&E facilities and the Type 2 MIUs.

A&E waiting times in the UK have increased substantially over recent years. This is also true for the South West of England. We take the example of a local NHS Trust, which, in 2016, operated one acute A&E hospital and seven MIUs. The A&E attendance at the local hospital was above the national average with approx. 40,000 attendances per 100,000 population, compared with 30,0000 per 100,000 population in England (Turner, 2015 as cited in Mustafee et al., 2017). Another factor contributing to overcrowding was the increased demand from tourists during the summer (by one estimate, the catchment population of the Trust increases by over 100,000 during this period). Analysis of secondary data on patient flow revealed that during the period between July 2015 and Jan 2016, almost 25% of patients that visited the A&E department had to wait for over 4 hours to be discharged (or admitted or transferred to another provider) following treatment ($\tilde{9}$500 patients). This figure was less than 1.5% for the MIUs. As the 4-hour standard applies to 95% of patients, Mustafee et al. (2017) revealed the seven MIUs met the 4-hour target, whereas the A&E department reported a high proportion of 4-hour breaches. Although the findings are local to a Trust in the South West, the breach rates represent the broader picture in terms of adherence to the 4-hour target nationally. For example, in February 2020, only 73% of patients were seen within four hours in Type 1 A&E departments, compared to 98.6% adherence at Type 3 facilities like the MIUs (see the Kings Fund report, 2020).

Nationally, around 9% patients who attend A&E are discharged without requiring treatment, and a further 32% receive guidance or advice only (NHS Digital 2019). Our discussions with the clinicians and other healthcare stakeholders (e.g., Quality Assurance, NHS Managers) revealed that a proportion of these patients could have had their healthcare needs met at a Tier-3 facility such as MIU or, in some cases, in Tier-1 facilities, e.g., pharmacists and dentists. However, as the patients may not be aware of the facilities that exist in their local MIUs (e.g., patients are seen by senior practitioner nurses, X-ray facilities and technicians are available), they usually choose to visit A&E departments as they are confident they will be seen and have their needs met. In our study reported here, we analyse the choice of A&E over MIU, given the patients are similarly informed, so this rules out the explanation that patients go to A&E because they are unaware of MIUs. Understanding this choice can reveal why patients are likely to go to A&E.

In 2016, we engaged with the local healthcare Trust to discuss ways of leveraging routine patient flow data that was being collected using A&E patient systems and ways of transforming this into actionable insights, with the objective of informing patients of the current wait times at both A&E departments and MIUs that were located close to them. A web-based application that made available wait time data from the A&E and the MIUs was by the IT team from the local Trust. This work is presented in Mustafee et al. (2017). Although the application meant that users could now have access to real-time data, this, however, did not provide user-specific information, e.g., MIUs that were closest to a user? Using a mobile app would allow us to provide directed information. Through the GPS facility of a mobile phone, we could identify a user's location. A real-time back-end platform could relay the A&Ewait-time information that it receives ever 5-15 minutes as per the request of the app. The architecture of the platform, which we call as NHSquicker, is presented in Mustafee et al. (2018). Considering the national picture on A&E wait times, it was felt that such a solution should have an underlying architecture that would enable it to scale regionally. This meant that we would require access to data from several Trusts; an informal networking organisation could help us realise this.

The IMPACT Network was founded in September 2016 through a collaboration between the University of Exeter Business School and the local Trust. The purpose of the network is to improve the delivery of health and care through applied research, knowledge dissemination and decision support. The NHSquicker platform and the NHSquicker app were co-developed by the network through several Trusts in Devon and Cornwall. The app allows patients needing treatment for urgent conditions to use their mobile phones to check live waiting times. The app is the information delivery mechanism that draws in the overarching NHSquicker platform, which serves as the information backbone. The app provides nudges, in the form of indirect suggestions, and informs patients of the urgent care services that are located in close proximity and moving them away from pressure points (usually A&E departments) to centres that are relatively less busy but have the capacity and the resources needed to meet urgent care needs (the MIUs).

The primary objective of NHSquicker is to shift demand from A&E departments to MIUs. The platform currently enables this by transforming real-time data on waiting time and providing nudges (Mustafee et al., 2018). Another objective is to increase the proportion of patients prepared to wait longer, even in MIU. However, because of the inherent preference of people towards A&E, what we observe is that even if MIU wait is lower, people tend to attend A&E.

This study focuses on how reducing information given to patients can influence the choices between A&E and MIU. Reducing information can come in two forms. First, one can give uncertainty information about waiting times (rather than the times themselves). Second, one can give qualitative shifts in the underlying probability distributions creating an ambiguous simulation.

We attempt to achieve the above by identifying the point (the indifference point) at which patients would switch from an A&E to an MIU due to longer waiting times being experienced at the former facility. Identification of the indifference point would allow the controlled release of wait time information in terms of precision and serve as an input to the nudge algorithm. The overall effect of this is the likely increase in the number of non-urgent patients that choose MIUs over A&Es.

3 Theory

In this section, we will present a model of ambiguity aversion that demonstrates how risk and ambiguity can be incorporated into an individuals decision problem. In particular, we show that with enough ambiguity aversion, a user may choose to go to the MIU (with a known waiting time) when a non-ambiguity averse individual would choose the A&E. The model developed here also provides a basis for the hypotheses in the following Hypothesis section.

The choice of location made by the agent is $x \in \{a, m\}$, which can be either a for A&E or m for MIU. Let the time of wait at the health location be given by $s_x \in \mathbb{R}_+$, and let $\sigma \in \sum$ be the time of the day (or the season). The state of the world is $(s_a, s_m, \sigma) \in \mathbb{R}_+^2 \times \sum$. The agent has a standard utility function $u(x, s_x)$ that is strictly decreasing in the second argument.

The agent has beliefs about s_x that are described by an additive probability distribution

π_x over $\Pi_x \subset \mathbb{R}_+$. For a full description of the choice model used see Kelsey and Eichberger (2014). These beliefs are partially ambiguous and we model the uncertainty utility as

$$V(x) = \delta\alpha(\sigma)\, min_{s_x \in \Pi_x} u(x, s_x) + \delta(1-\alpha(\sigma)) max_{s_x \in \Pi_x} u(x, s_x) + (1-\delta)\, Eu(x, s_x).$$

The confidence in the belief is modeled by $(1-\delta)$, with $\delta = 1$ means complete ambiguity and $\delta = 0$ denoting no ambiguity. The agent knows that the possible times are within a subset of real times (partial ambiguity). For instance, waiting time at the A&E will be less than 24 hours. The agent's attitude to ambiguity is $\alpha(\sigma)$. The higher the α the more ambiguity-averse the decision-maker will be. At the time of the choice of x the agent knows σ. The agent maximizes his utility by choosing $x^* \in arg \max V(x)$.

Example 1 $\Pi_a = \Pi_m = \{30, 60, 90\}$, $\pi_a(30) = \pi_a(60) = \pi_a(90) = 1/3$, $\pi_m(30) = \pi_m(90) = 0$, $\pi_m(60) = 1$, $\sigma = 1, \delta = 1/2, \alpha = 1/2$.

First, $V(m) = u(m, 60)$. Next, we have $V(a) = \frac{1}{4}u(a, 30) + \frac{1}{4}u(a, 90) + \frac{1}{2}Eu(a, s_a)$, since $u(x, s_x)$ is decreasing in s_x. We also have $Eu(a, s_a) = \frac{1}{3}u(a, 30) + \frac{1}{3}u(a, 60) + \frac{1}{3}u(a, 90)$. Thus,

$$V(a) = \frac{5}{12}u(a, 30) + \frac{1}{6}u(a, 60) + \frac{5}{12}u(a, 90).$$

Example 2 $\Pi_a = \Pi_m = \{30, 60, 90\}$, $\pi_a(30) = \pi_a(60) = \pi_a(90) = 1/3$, $\pi_m(30) = \pi_m(90) = 0$, $\pi_m(60) = 1$, $\sigma = 1, \delta = 0, \alpha = 1$.

In this example, there is no ambiguity so

$$V(a) = Eu(a, s_a) = \frac{1}{3}u(a, 30) + \frac{1}{3}u(a, 60) + \frac{1}{3}u(a, 90).$$

Example 3 $\Pi_a = \Pi_m = \{30, 60, 90\}$, $\pi_a(30) = \pi_a(60) = \pi_a(90) = 1/3$, $\pi_m(30) = \pi_m(90) = 0$, $\pi_m(60) = 1$,$\sigma = 1, \delta = 1/2, \alpha = 1$.

In this example, the agent is fully pessimistic. We now have $V(a) = \frac{1}{2}u(a, 60) + \frac{1}{2}Eu(a, s_a)$, thus

$$V(a) = \frac{1}{6}u(a, 30) + \frac{1}{6}u(a, 60) + \frac{2}{3}u(a, 90).$$

Note that if $u(a, 60) = \frac{1}{2}[u(a, 30) + u(a, 90)]$ and $u(a, s) > u(m, s)$ for all s, then in Example 2, the agent would prefer choosing a. However, in Example 3, it is quite possible that the agent would choose m due to different ambiguity. For example, if we have $u(m, s) = -s$ and $u(a, s) = 1 - s$, then this is the case even with risk neutrality over waiting time.

4 Hypotheses

We ran an experiment where we elicit preferences over waiting times between the A&E and MIU. Over here we are assuming that a key determinant of choice for the decision makers is how early they they are seen by the health provider. This is an important factor in the health outcome of the patient.

Hypothesis 1 *Given the same waiting time, subjects exhibit a preference for A&E over MIU.*

In our notation, Hypothesis 1 states $u(a, s) > u(m, s)$ for all s. This reflects the outcome we observe that from the NHS data regarding A&E attendance and overcrowding. This hypothesis will check if individuals in fact exhibit a preference for the A&E over MIU all else being equal.

Hypothesis 2 *Subjects are risk averse. If the waiting time to be seen by a health practitioner at A&E is uncertain with known probabilities (while MIU waiting time is certain), then the subjects will prefer MIU over A&E relative to when the A&E waiting time is equal to its expectation.*

For the possibilities in our experiment for risk-aversion, utility must satisfy $u(x, 60) > \frac{1}{2}[u(x, 30) + u(x, 90)]$ for $x = a, m$. Furthermore, as in Hypothesis 2, if $u(a, 30) = u(m, m_{30})$ and $u(a, 90) = u(m, m_{90})$, then $u(m, \alpha \cdot m_{30} + (1 - \alpha) \cdot m_{90}) > \alpha \cdot u(a, 30) + (1 - \alpha)u(a, 90)$. Thus, if $u(m, z) = \alpha \cdot u(a, 30) + (1 - \alpha)u(a, 90)$, then $z > \alpha \cdot m_{30} + (1 - \alpha) \cdot m_{90}$.

Hypothesis 3 *Subjects are ambiguity averse. If the waiting time to be seen by a health practitioner at A&E is uncertain with* **unknown** *probabilities (while MIU waiting time is certain), then the subjects will prefer MIU over A&E relative to when both waiting times are known with certainty and when A&E waiting times are uncertain with known probabilities.*

If $u(m, m_{amb}) = V(a)$ and $u(m, m_{uncer}) = Eu(a, s_a)$, then $u(m, m_{amb}) < u(m, m_{uncer}) < u(m, \pi_{30} \cdot m_{30} + \pi_{90} \cdot m_{90})$. This implies $m_{amb} > m_{uncer} > \pi_{30} \cdot m_{30} + \pi_{90} \cdot m_{90}$.

Here clearly not knowing the probabilities of the waiting times will affect the choice. The decision maker will chose the option which has less ambiguity. As agents are made aware of the likelihood of the time required to be seen by a health professional, subjects will choose to visit MIU rather than A&E.

5 Design and Procedure

We framed the decision problem as the subject is an individual who suffers from sudden lower back pain has to decide whether to go to the local Accident and Emergency (A&E) or the local Minor Injury Unit (MIU). The local A&E has a wait time t_a and the local MIU has waiting time of t_m.

We had subjects go through two stages: stage 1 was a certainty comparison stage and stage 2 was either a risk or ambiguity stage. In the first stage we asked subjects to compare a known t_a to a known t_m in a series of questions via a dynamic algorithm designed to determine the indifferent point.

This is done by keeping the wait time at the A&E fixed and varying the MIU option. For example, the first decision problem is between a 60 minute wait for the A&E and a 80 minute wait for the MIU. If the A&E option is preferred, then the next comparison is 40 minute wait time for MIU. If MIU is selected then MIU option of 60 is offered. If the A&E is selected then the MIU option of 50 is offered. If A&E is then selected then 55 is the MIU option. We repeat this until, say MIU option was accepted at 52 and rejected at 54. The algorithm would then assign the indifferent point to be 53.

In stage 2, we give a possible gamble for the value of t_a and like in stage one use a dynamic algorithm to determine the indifference point for a value of t_m. This gamble was either a case of risk where the lottery for t_a was given or the treatment was of ambiguity where the probabilities were subjective.

A total of 169 subjects participated in the experiment among 4 treatments (2 x 2 design) run with a total of 6 sessions. There were two flat fee sessions – one for each of risk and ambiguity. There were also four incentive sessions – two for each of risk and ambiguity. [1] The experiment was conducted in the FEELE lab at the University of Exeter and subjects were undergraduate students.

The timing of the experiment was as follows. At the start of the experiment, subjects were randomly seated and then read through a set of paper instructions for stage 1(see Appendix). Then completed stage 1 and stage 2 instructions were read. Afterwards, they completed stage 2. The subjects completed a questionnaire and were paid.

The experiment was written in z-Tree (Fischbacher, 2007) and we used the ORSEE recruiting system (Greiner, 2015) for recruiting subjects. Subjects received a show-up fee of

[1] We had 59 subjects in our ambiguity and incentives sessions, 28 subjects in our ambiguity and flat fee session, 55 in our risk and incentives sessions, and 27 subjects in our risk and flat fees session.

£5. The experiment lasted approximately 40 minutes and the average payment for incentive sessions (including show up fee) was approximately £13.50. It ranged from £4.2 pounds to £32.42 pounds. In the flat fee treatments, subjects were paid 10 pounds (including the 5 pounds show up fee).[2]

6 Results

We start the result section by examining the stage 1 decision of setting an indifference point between the A&E and MIU in terms of waiting time at the MIU. The decision problem is identical between treatments in stage 2 and we would expect no difference. However, the problem may vary on whether flat fees or monetary incentives are used, since choice of payment affects payoffs. In Table 1, we see the average indifference point for switching between MIU and A&E for each treatment and each possible waiting time at the A&E. Notice that the average is below the waiting time at the A&E. This indicates that the A&E is preferred to the MIU. This higher number (indifference point) for the MIU indicates that the MIU is preferred less.[3]

Notice that roughly there **does** seem to be a difference between flat fees and incentives with incentives at a higher indifference point. One reason that flat fees could induce a stronger preference for the A&E is that incentives causes subjects to focus more on the waiting time than the type of urgent care. There also appears to be a difference between (albeit smaller) between ambiguity and risk. Given that this is from an identical initial stage, it indicates a random difference between the subjects or other conditions that we did not account for (time of session for instance). We hence would need to adjust for this in the analysis.

In Table 2, we present three regressions that examine the indifference points in part 1 of the experiment. They are of the form:

$$\texttt{vdiffx} = \beta_0 + \beta_1 \texttt{flat}$$

Variable vdiffx is equal to x minus the corresponding indifferent point (where x equals 30, 60, or 90). Hence, the dependent variables are vdiff30, vdiff60, and vdiff90. So, for instance, vdiff30 equals $30 - AE30$. Larger difference indicates greater preference for A&E where AE30, AE60, and AE90 are the indifference point in terms of minutes at the MIU to the

[2]The flat fee sessions ran slightly faster than the incentive sessions.

[3]Waiting time is a economic bad. Hence, a higher negative value corresponds to a less attractive option.

Treatment	A+E Wait time 30	60	90
Ambiguity + Flat fees	20	45.6	72
Risk + Flat fees	22.8	49.2	76
Ambiguity + Incentives	24.3	51.4	79.4
Risk + Incentives	26.5	54.8	84.1
Combined	24.1	51.2	79.2

Table 1. *Stage 1 indifference points of switching between MIU and A&E in waiting time in minutes for the MIU.*

	(1)	(2)	(3)
	vdiff30	vdiff60	vdiff90
flat	4.014^{**}	5.689^{*}	7.756^{*}
	(1.506)	(2.377)	(3.182)
_cons	4.632^{***}	6.956^{***}	8.289^{***}
	(0.859)	(1.356)	(1.815)
N	169	169	169

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. *Regression determining preference for A&E compared to MIU. The dependent variables are vdiff30, vdiff60, and vdiff90. Variable vdiffx is equal to x minus the indifferent point (where x equals 30, 60, or 90), for instance, vdiff30 equals* $30 - AE30$. *Larger difference indicates greater preference for A&E. Flat equals 1 when payments are a lump sum, while flat equals 0 when payments are incentive based.*

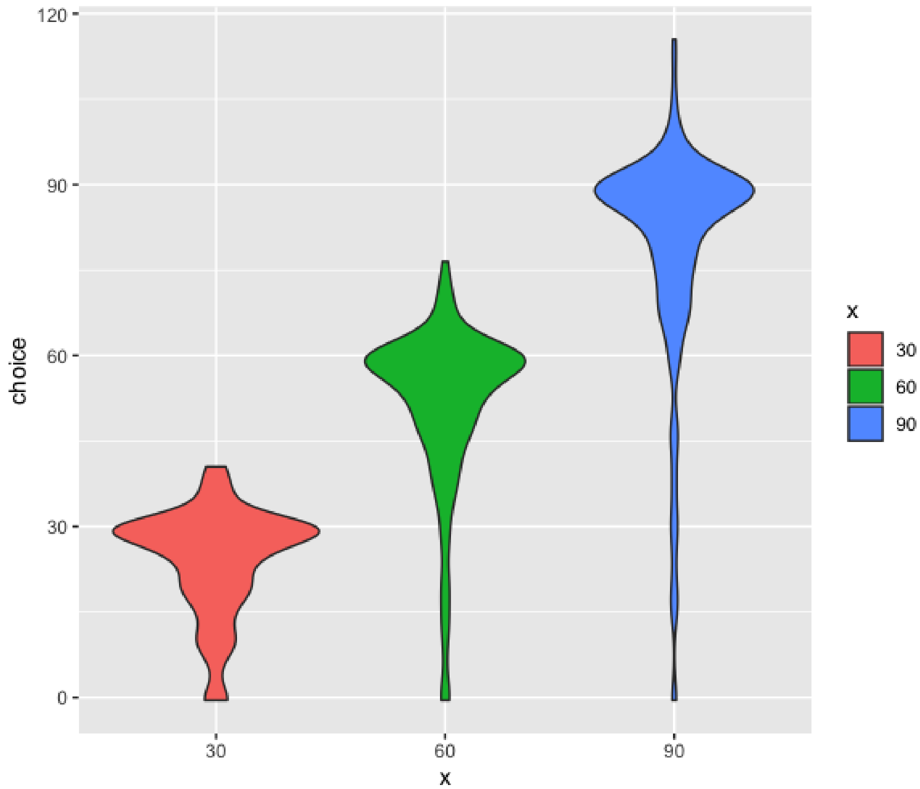

Figure 1. *Violin plot of the stage one indifference points between the MIU and A&E in waiting time minutes for the MIU. The x-axis corresponds to the certain waiting time at the A&E of either 30, 60 or 90 minutes.*

corresponding time at the A&E (that is, 30, 60, 90 minutes). Flat equals 1 when payments are a lump sum (not incentivised), while flat equals 0 when payments are incentive based.

In all three regressions, we find that the constant is positive and significant at the 0.1% level. This means that subjects preferred the A&E. This is consistent with Hypothesis 1. We note the coefficient increases between regressions based upon waiting time, but not quite proportional (linear).

We also find that the flat variable is positive and significant for the 30, 60, and 90 minutes waiting times to the 1%, 5% and 5% levels, respectively. This means that with flat fees the preference for the A&E is stronger than with incentives.

Result 1 *Subjects demonstrate a strong preference for the A&E over the MIU.*

Result 1 confirms Hypothesis 1. While on average subjects preferred the A&E in the first stage, there were exceptions as we can see in the violin plots in Figure 1. More specifically,

Probability α for A&E wait time $\alpha 30$ and $(1-\alpha)90$	0.25	0.50	0.75
Ambiguity Indifference Point –	58.7	53	46.7
Uncertainty Indifference Point –	66.3	52.3	39.2
Implied Risk Neutral Indifference Point from Decision 1	65.4	51.7	37.9
Expected A&E waiting time	75	60	45

Table 3. *Stage 2 indifference points of switching between MIU and A&E in waiting time in minutes for the MIU.*

out of the 169 subjects, 32 subjects preferred the MIU when the waiting time was 30 minutes, while 29 preferred the MIU when the waiting time was 60 minutes, and 30 preferred the MIU when the waiting time was 90 minutes.

Looking at Table 3, we calculate what the implied indifferent point for each of the uncertainty conditions based upon subject responses in part 1 of the experiment. Formally, the indifference point for α is $\alpha AE30 + (1-\alpha)AE90$. All of these numbers are virtually the same as the uncertainty indifference points, actually just slightly below. This means if anything subjects behave as if they are slightly risk loving so calling them risk-neutral is reasonable. This leads us to Result 2.

Result 2 *Subjects display risk neutrality for the waiting time of the A&E in terms of the MIU waiting time.*

Result 2 rejects Hypothesis 2. The violin plot of Figure 2 further supports this result with visual evidence.

Interestingly, in Table 3 the Ambiguity switching point is higher that the implied risk neutral point when $\alpha = .75$ and lower when $\alpha = .25$. To further examine this while controlling for individual preferences for the A&E, we confirm this result with the following two regressions in Table 4:

$$\texttt{AE75} = \beta_0 + \beta_1 \texttt{AE50} \;\; + \beta_2 \; \texttt{ambiguity}$$

$$\texttt{AE25} = \beta_0 + \beta_1 \texttt{AE50} \;\; + \beta_2 \; \texttt{ambiguity}$$

Here `AE25`, `AE50`, and `AE75` represent the indifference points in terms of MIU waiting times for when the uncertain probability of a 30 minutes wait at the AE is 25, 50, and 75 percent, respectively. `Ambiguity` is a dummy variable for the ambiguity treatments. In the ambiguity

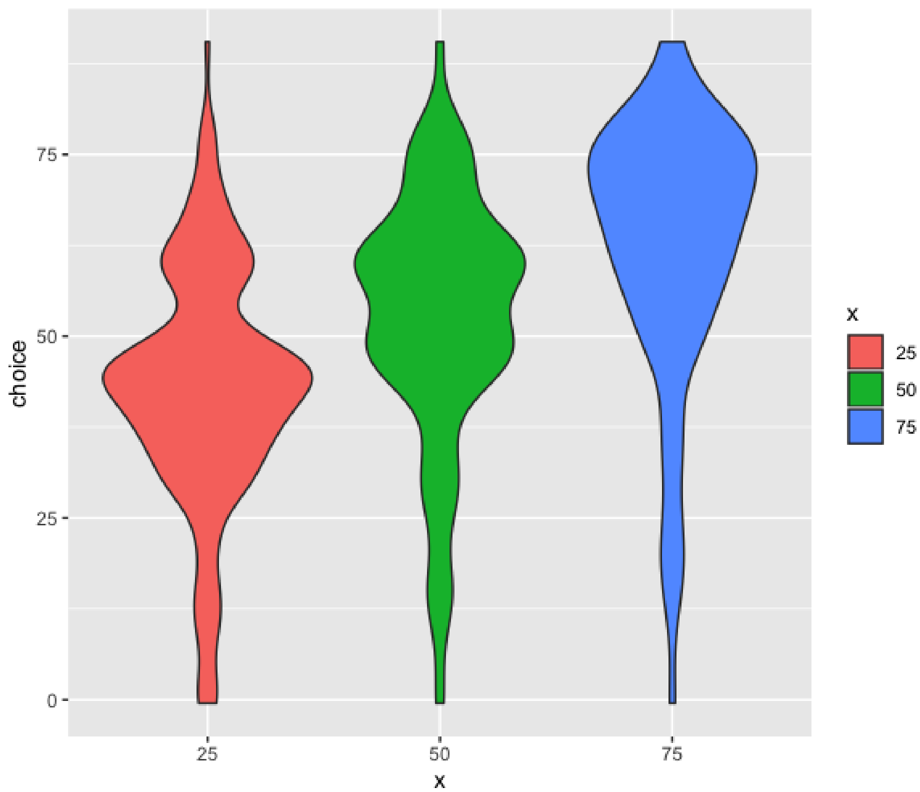

Figure 2. *Violin plot of the stage two indifference points between the MIU and A&E in waiting time minutes for the MIU. The x-axis corresponds to the A&E uncertain waiting time of x chance of 90 mins and $(1-x)$ of 30 minutes, where x can be 25, 50, or 75. Note the expectation of waiting time is 45, 60, and 75, respectively.*

treatments, `AE50`, `AE25`, and `AE75`. In the first instance for `AE50`, the subjects were given no information about the likelihood of the waiting time, in case of `AE25`, subjects were told that that there were fewer personnel at AE compared to the initial state and finally for `AE75` the subjects were told that the A&E hired more personnel in comparison to the initial state.

AE50 captures the relative preference for the A&E. This was roughly similar between the ambiguity and uncertainty treatments so a useful baseline. The results of the regression is that the AE50 baseline is a significant predictor of both AE25 and AE75 with a similar magnitude. The key insight is ambiguity variable. It is significant in both regressions and positive in AE75 and negative in AE25 with similar absolute magnitudes. This points toward ambiguity aversion with shorter waiting times and ambiguity loving with longer waiting times.

	(1)	(2)
	$AE25$	$AE75$
$AE50$	0.804***	0.678***
	(0.0506)	(0.0480)
ambiguity	-8.121***	7.127***
	(1.745)	(1.653)
_cons	24.20***	3.682
	(2.931)	(2.777)
N	169	169

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. *The effect of ambiguity on choice. Variable AEx is the indifference point of x% of 30 minutes waiting time and (1-x)% of 90 minutes waiting at the A&E in terms of waiting time at the MIU. The dummy variable ambiguity is equal to 1 in the ambiguity treatments.*

Result 3 *Subjects are ambiguity averse when waiting times are relatively short and ambiguity seeking when waiting times are relatively long.*

Interestingly Result 3 shows that Hypothesis 3 only applies only waiting times are relatively short rather than for all waiting times.

This may be surprising since in many experiments, ambiguity aversion is found in many circumstances. This means that with health services, patients are pessimistic with short waiting times and optimistic with long waiting times. Pessimism means that while there is an x chance of a delay, the pessimists think the chance is much higher than x. The optimists think the chance of delay is much lower than x. An alternative explanation is that it could be that the waiting time is not completely exogenous. In more serious cases, the A&E would move someone in front of the queue rather than have them wait a long time and in such serious cases there could a stronger advantage of the A&E. Of course, both the experiment and NHSquicker are meant for urgent but not life-threatening care, but there could be some carryover.

One other explanation is that the wording of our ambiguity might be interpreted differently than what we give the underlying odds. In this wording, we state that there is a lower/higher probability of the shorter waiting time. While it may be most natural to take a uniform prior of change (leaving the probability at 25% or 75 %), it may be that subjects take this as only minor changes say (leaving the probability at 40% or 60 %). We cannot rule this out with the current experimental design.

7 Conclusion

We ran an experiment where we elicit preferences over waiting times between the A&E and MIU. When there is certainty about the waiting time information, we find there is a strong general preference for A&E in the experiment. Still, people respond to time information in that for longer waiting time in A&E, people switch to the MIU. When uncertainty in regards to the waiting time is introduced, there is a still a switching point from A&E to MIU. This above point holds when waiting time is uncertain but some approximate time is communicated. When waiting time at A&E is expected to be long, we find that it is optimal to give as much precise information as possible. When waiting time at A&E is expected to be short, we find that it is optimal not to give precise times but state that waiting time is short.

With the objective of trying to nudge people to the MIU, we should release information in such a way as to generate higher indifference points. As such, our results have clear policy implications. Namely, the health services should be vague during non-busy periods but precise in busy periods. This is surprisingly better than giving all the information available and better than not using the app.

To conclude, our research will inform stakeholder decision-making at both the operational level, e.g., individual UK National Health Service (NHS) Trusts, and at the strategic/policy level, e.g., NHS Digital and the UK Department of Health and Social Care, about whether to make available wait time data to the intended users of the systems (the patients) and if so, the precision of this information.

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A Instructions

A.1 Ambiguity

You are home in the early evening. You slip and fall hurting your shoulder. You are in severe pain and have minimal mobility. You suspect your shoulder has been dislocated or broken. You have two choices either to go to local Accident and Emergency (A and E) at Royal Devon and Exeter or the Minor Injury Unit NHS (NHS MIU) in town in Exeter. At the Accident and Emergency you will be seen by a doctor on call and at the Minor Injury Unit the nurse in charge will see you. You will be given a series of choices where you have to decide whether you want to go to the Accident and Emergency unit or to the Minor Injury Unit. In your choices you will also be informed about the time you need to wait at the A and E and or the Minor Injury Unit NHS before your injury is seen by the health practitioner.

Your actual payoff will be 120 minus the time to see health practitioner (doctor or nurse). To decide your payoff the computer will learn about your preferences from your decisions. At the end there will be a decision/situation given which the computer will take for you. From this choice made by the computer, you will know the time it will take to see your doctor.

Decision 1: You will get three sequences of choices and asked to choose between going to A and E or NHS MIU for your shoulder injury. Both are equidistant from your house. For each sequence please make your choices till the computer asks you to stop. Example: If you go to A and E you will be seen by the resident doctor in 10 minutes and if you go to MIU you will be seen in 15 minutes by the practitioner nurse. Where will you go, A and E or MIU?

Decision 2: You will get three sequences of choices and asked to choose between going to A and E or NHS MIU for your shoulder injury. Both are equidistant from your house. For each sequence please make your choices till the computer asks you to stop. Example: If you go to A and E you will be seen by the resident doctor in 10 minutes or in 30 minutes and if you go to MIU you will be seen in 15 minutes by the practitioner nurse. Where will you go, A and E or MIU?

A.2 Risk

You are home in the early evening. You slip and fall hurting your shoulder. You are in severe pain and have minimal mobility. You suspect your shoulder has been dislocated or broken. You have two choices either to go to local Accident and Emergency (A and E) at Royal Devon and Exeter or the Minor Injury Unit NHS (NHS MIU) in town in Exeter. At the Accident and Emergency you will be seen by a doctor on call and at the Minor Injury Unit the nurse in charge will see you. You will be given a series of choices where you have to decide whether you want to go to the Accident and Emergency unit or to the Minor Injury Unit. In your choices you will also be informed about the time you need to wait at the A and E and or the Minor Injury Unit NHS before your injury is seen by the health practitioner.

Your actual payoff will be 120 minus the time to see health practitioner (doctor or nurse). To decide your payoff the computer will learn about your preferences from your decisions. At the end there will be a decision/situation given which the computer will take for you. From this choice made by the computer, you will know the time it will take to see your doctor.

Decision 1: You will get three sequences of choices and asked to choose between going to A and E or NHS MIU for your shoulder injury. Both are equidistant from your house. For each sequence please make your choices till the computer asks you to stop. Example: If you go to A and E you will be seen by the resident doctor in 10 minutes and if you go to MIU you will be seen in 15 minutes by the practitioner nurse. Where will you go, A and E or MIU?

Decision 2: You will get three sequences of choices and asked to choose between going to A and E or NHS MIU for your shoulder injury. Both are equidistant from your house. For each sequence please make your choices till the computer asks you to stop. Example: If you go to A and E you will be seen by the resident doctor in 10 minutes with probability 1/3 or in 30 minutes with probability 2/3. If you go to MIU you will be seen in 15 minutes by the practitioner nurse. Where will you go, A and E or MIU?

References

Abdellaoui, M., P. Klibanoff, and L. Placido (2015): "Experiments on compound risk in relation to simple risk and to ambiguity," *Management Science*, 61(6), 1306–1322.

Ahn, D., S. Choi, D. Gale, and S. Kariv (2014): "Estimating ambiguity aversion in a portfolio choice experiment," *Quantitative Economics*, 5(2), 195–223.

Attema, A. E., H. Bleichrodt, and O. L'Haridon (2018): "Ambiguity preferences for health," *Health Economics*, 27(11), 1699–1716.

Ben-Elia, E., and E. Avineri (2015): "Response to travel information: A behavioural review," *Transport reviews*, 35(3), 352–377.

Chen, Y., P. Katuščák, and E. Ozdenoren (2007): "Sealed bid auctions with ambiguity: Theory and experiments," *Journal of Economic Theory*, 136(1), 513–535.

Cubitt, R., G. van de Kuilen, and S. Mukerji (2019): "Discriminating Between Models of Ambiguity Attitude: a Qualitative Test," *Journal of the European Economic Association*, 18(2), 708–749.

Di Somma, S., L. Paladino, L. Vaughan, I. Lalle, L. Magrini, and M. Magnanti (2015): "Overcrowding in emergency department: an international issue," *Internal and emergency medicine*, 10(2), 171–175.

Eichberger, J., and D. Kelsey (2014): "Optimism and Pessimism in Games," *International Economic Review*, 55(2), 483–505.

Einhorn, H. J., and R. M. Hogarth (1985): "Ambiguity and uncertainty in probabilistic inference.," *Psychological Review*, 92(4), 433.

Fischbacher, U. (2007): "z-Tree: Zurich toolbox for ready-made economic experiments," *Experimental economics*, 10(2), 171–178.

Halevy, Y. (2007): "Ellsberg revisited: An experimental study," *Econometrica*, 75(2), 503–536.

Kelsey, D., and S. Le Roux (2017): "Dragon slaying with ambiguity: theory and experiments," *Journal of Public Economic Theory*, 19(1), 178–197.

Kocher, M. G., A. M. Lahno, and S. T. Trautmann (2018): "Ambiguity aversion is not universal," *European Economic Review*, 101, 268–283.

Li, C., U. Turmunkh, and P. P. Wakker (2019): "Trust as a decision under ambiguity," *Experimental Economics*, 22(1), 51–75.

March, J. G. (1987): "Ambiguity and accounting: The elusive link between information and decision making," *Accounting, organizations and society*, 12(2), 153–168.

Mustafee, N., J. H. Powell, and A. Harper (2018): "RH-RT: a data analytics framework for reducing wait time at emergency departments and centres for urgent care," *Proceedings of the 2018 SCS Spring Simulation Multi-Conference*, pp. 100–110.

Mustafee, N., J. H. Powell, S. Martin, A. Fordyce, and A. Harper (2017): "Investigating the use of real-time data in nudging patients' Emergency Department (ED) attendance behaviour," *Proceedings of the 2017 SCS Spring Simulation Multi-Conference*, pp. 1–9.

Muthukrishnan, A., L. Wathieu, and A. J. Xu (2009): "Ambiguity aversion and the preference for established brands," *Management Science*, 55(12), 1933–1941.

Peysakhovich, A., and U. R. Karmarkar (2016): "Asymmetric effects of favorable and unfavorable information on decision making under ambiguity," *Management Science*, 62(8), 2163–2178.

Qi, J., M. Sim, D. Sun, and X. Yuan (2016): "Preferences for travel time under risk and ambiguity: Implications in path selection and network equilibrium," *Transportation Research Part B: Methodological*, 94, 264–284.

Stecher, J., T. Shields, and J. Dickhaut (2011): "Generating ambiguity in the laboratory," *Management Science*, 57(4), 705–712.

The King's Fund (2020): "What's going on with AE waiting times?," https://www.kingsfund.org.uk/topics/emergency-care, Last Accessed: February 2021.

Voorhoeve, A., K. Binmore, A. Stefansson, and L. Stewart (2016): "Ambiguity attitudes, framing, and consistency," *Theory and Decision*, 81(3), 313–337.